Accuracy Assessment of land use maps classification based on remote sensing and GIS techniques

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Abstract. The need to classify sentinel-2 satellite images to create land use /land cover (LULC) are essential to analysis the processes of environment problems and to improve living conditions. Hence, this research aims to assess of accuracy classification by Support Vector Machine (SVM) approach to create LULC maps from sentinel-2 satellite images using remote sensing and GIS. The selected study area for this research is Baghdad city because of it has a unique political stability and due to rapid urbanization that lead to rise additional request for natural resources and affected on LULC in Baghdad city. After preprocessing and processing of satellite images, thematic maps were created and classified into five main classes based on visual interpretation and visit the field of the study area containing: urban, vegetation, soil, asphalt roads, and water bodies. The results showed that classification accuracy assessment of SVM algorithm are acceptable because of overall accuracy and Kappa index equal (88%, 0.84) respectively.

1 INTRODUCTION

The process of mapping LULC holds significant importance in various fields such as environmental management, agriculture, urban planning, and disaster management [1]. The utilization of remote sensing, specifically satellite photography, has become vital for the comprehensive mapping of LULC on a global scale [2]. The Sentinel-2 satellite, which was deployed in 2015 under the auspices of the European Space Agency (ESA), offers a considerable degree of geographical resolution, temporal precision, and spectral band coverage. Consequently, it serves as a very advantageous instrument for the purpose of (LULC) mapping [3, 4]. Numerous studies have provided evidence regarding the efficiency of Sentinel-2 imagery in effectively categorizing and delineating land cover. As an example, a study conducted by [5, 6] conducted a comparison of (LULC) obtained from Sentinel-2 and Landsat-8 images. The results of this study showed that Sentinel-2 data can serve as a feasible alternative for mapping purposes in coastal regions. Machine learning techniques were effectively utilized on Sentinel-2 images in order to attain precise land cover maps. Furthermore, a multi-temporal classification system utilizing Sentinel-2 data was proposed by [7, 8], which demonstrated promising outcomes in the identification of various land cover classes. Recent studies conducted by researchers [9, 10] have emphasized the favorable influence of Sentinel-2 in the observing of (LULC), particularly in developing nations.

The objective of this study is to apply remote sensing and (GIS) to classify Sentinel-2 images to extract LULC maps for Baghdad city and assess the classification accuracy for Support Vector Machine algorithm.

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2 MATERIALS AND METHODOLOGY

2.1 STUDY AREA

In this research, Baghdad city was chosen as case study because it has a high population density and continuous urban growth. Also, it has a great diversity land uses are of a clear diversity with Longitude (44˚12΄ E) to (44˚33΄ E) and Latitude (33˚9΄ N) to (33˚30΄ N) and data sets are projected in UTM projection with zone number 38 and WGS 84 datum [11]. The city is crossed by the Tigris River and split into two groups: Karkh and Rusaffa as shown in Figure (1).

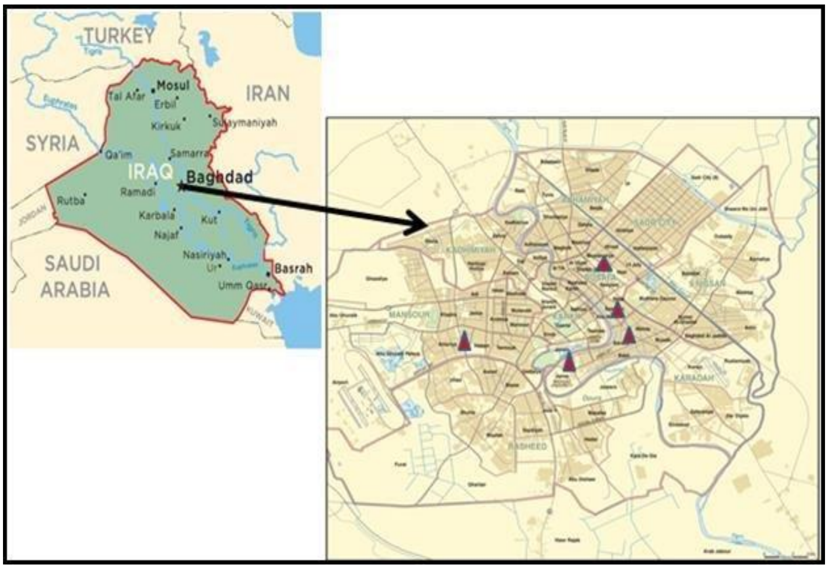

Fig. 1. study area Map.

2.2 MATERIALS

In this research, Sentinel images were used because of it is free and has spatial resolution (10m). Two images were covered the study area and pre-processed to correct of atmospheric .The images were taken in (Oct, 2023) from USGS where cloud-free as shown in figures (2, 3 and 4).

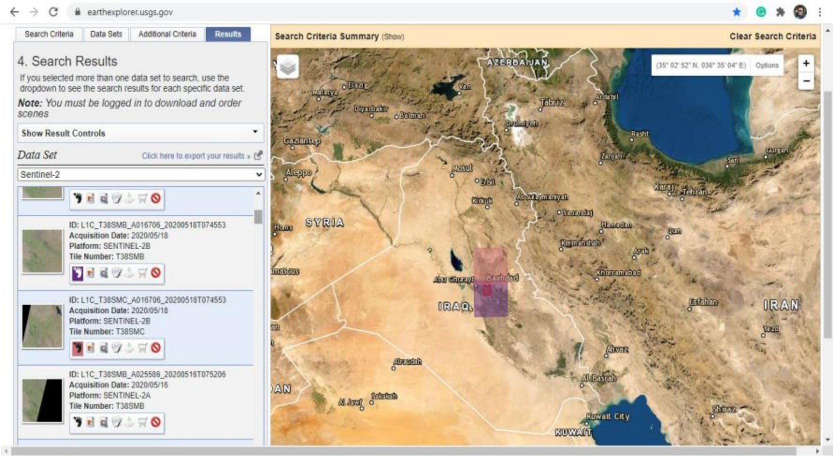

Fig. 2. USGS website

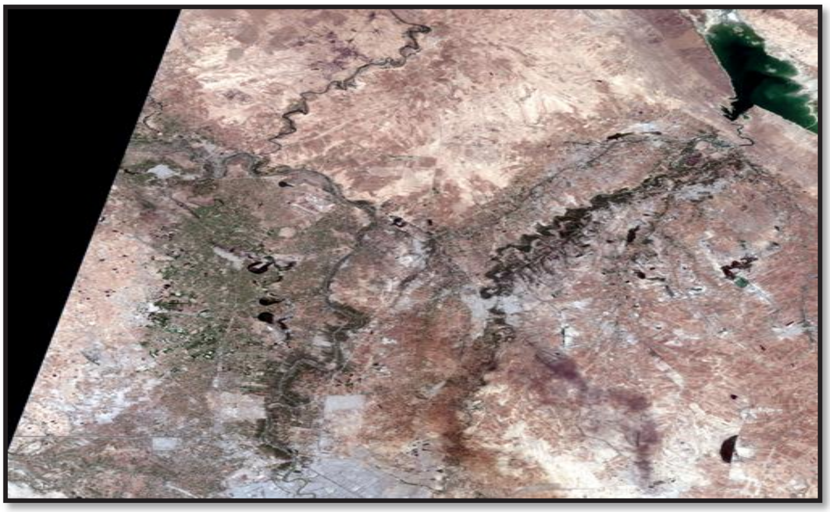

Fig. 3. Sentinel 2B image (1) (USGS)

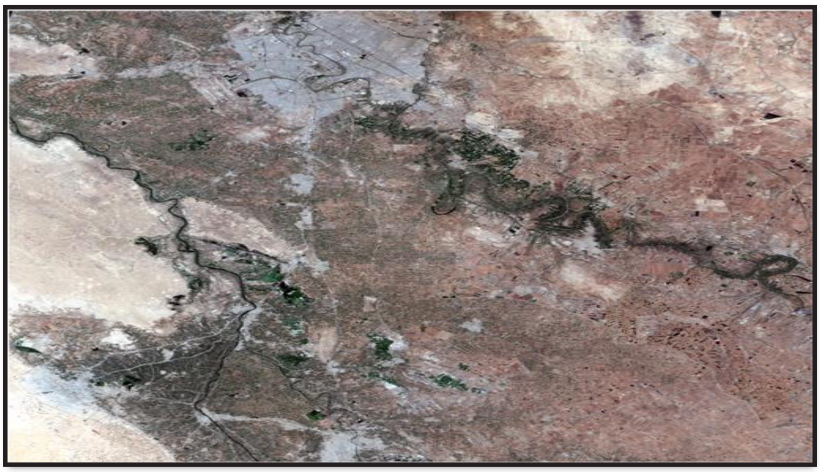

Fig. 4. Sentinel 2B image (2) (USGS)

2.3 Research Methodology

The methodology employed in this study encompasses a sequence of processing processes as shown in figure (5) through the utilization of remote sensing and GIS.

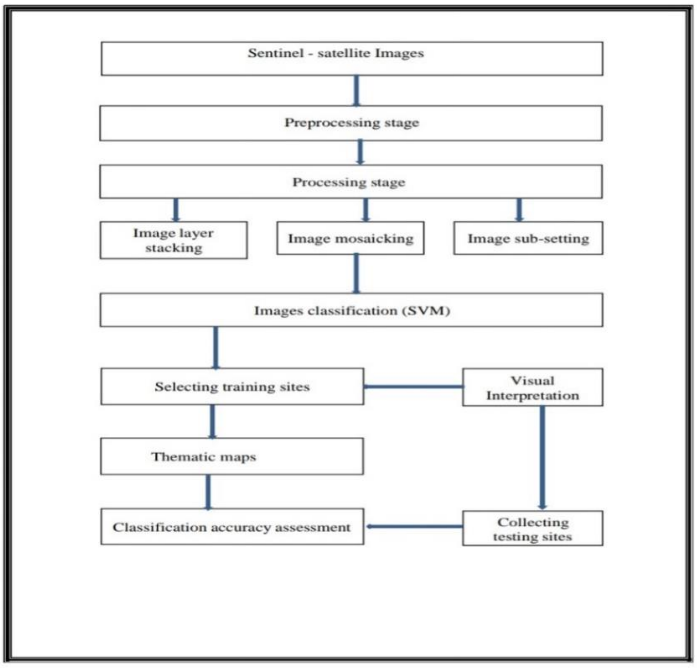

Fig. 5. The schematic of research methodology

There are several processing for these images that can be explained as following:

2.3.1 Mosaicking of Satellite Images process:

After perform layer stacking that aims to collect all bands in a single file for easy opening the image in the program and accelerate the processing using composite bands tool in ARC GIS 10.8softwar[12, 13]. Image mosaicking is performed according to a standard system of coordinates reported in meta-data as shown in figure (6).

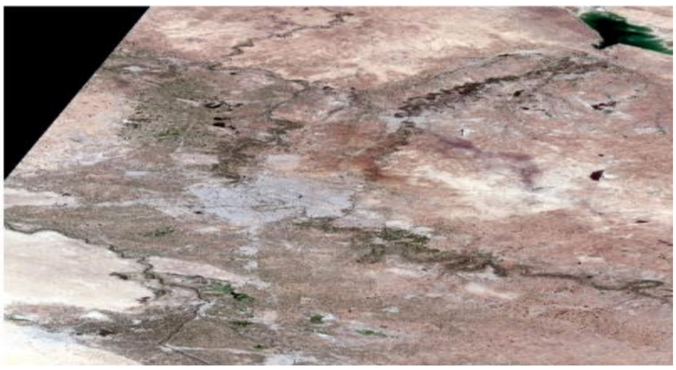

Fig. 6. Mosaicking Sentinel-2 images for the study area

2.3.2 Image sub-setting process:

The image is sub-setting to the square size boundary and this process is done using the shape file clipping data tools in ArcGIS 10.8 as shown in figure 7.

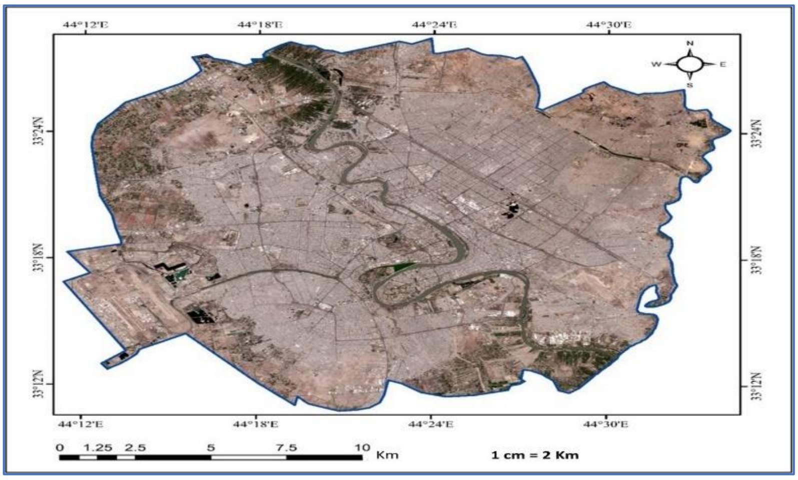

Fig. 7. Sub-setting of image.

2.3.3 Support Vector Machine (SVM) Algorithm:

SVM are frequently working in both classification and regression [14]. It operates by identifying the optimal hyper plane that effectively divides distinct classes within a feature space of high dimensionality as shown in figure (8) [15, 16]. The primary concept underlying (SVM) is to convert the input data into a feature space of larger dimensionality, wherein the classes can be separated by a linear boundary. Subsequently, the algorithm proceeds to find the hyper plane that optimizes the margin between the different classes. The margin refers to the spatial separation between the hyper plane and the closest data points belonging to each class. This feature enables (SVM) to possess a resilient decision boundary that exhibits strong generalization capabilities when applied to data that has not been previously seen [17, 18 19]. When faced with situations where the classes cannot be separated linearly, (SVM) employ a method known as the kernel trick (SVM) employ different kernel functions such as linear and polynomial [20,21].

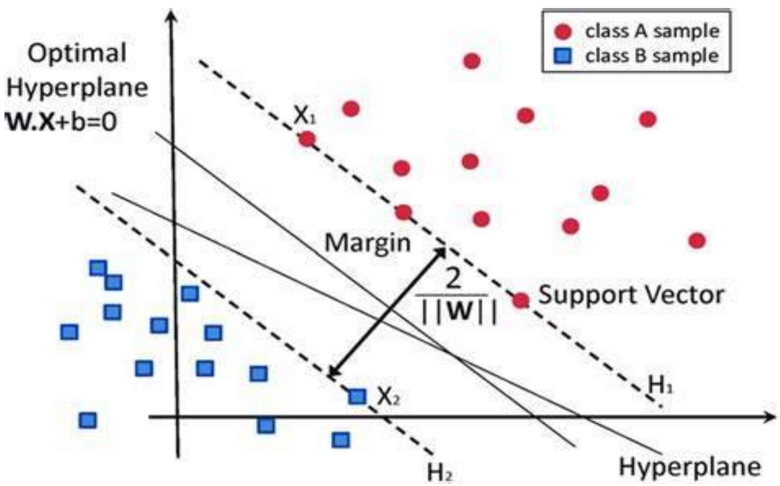

Fig. 8. An illustration of SVM concept for land cover classification [21].

The training sites were obtained utilizing ENVI 5.3 software to determine polygons representing the region of interest (ROIs) with each class and afterwards categorized these ROIs to create a map of LU/LC for a part of Baghdad city Iraq. The following stage entails identifying testing sites within the research area that were critical in determining the accuracy evaluation with each classification algorithm and validating producer and user classification accuracy. Ground truth samples are usually obtained from test locations, and the purer the ground truth samples, the more accurate the results. Using office work from satellite imagery, it able to gather the testing sites for this analysis.

2.3.4 Evaluation performance Methods

The accuracy evaluation is the last step in the processing of satellite images by which it is possible to check the accuracy of the results obtained. Accuracy assessment is a key phase in the process of evaluating the performance of a classification model [22]. It entails comparing the outputs of the classification model to a set of reference data that represents the genuine distribution of LU/LC classifications. The first stage in accuracy assessment is to gather reference data that represents the genuine distribution of LU/LC classes in the studied area. The acquisition of this information can be facilitated by utilizing ground truth data gathered by field surveys or other credible sources, such high-resolution imaging or pre-existing maps. The subsequent procedure involves the generation of a confusion matrix, which serves as a tabular representation for comparing the classification outcomes with the reference data. Various accuracy measures can be computed based on the data delivered in the confusion matrix. The overall accuracy (OA) refers to the ratio of accurately categorized pixels in the entirety of the image [23, 24]. The calculation involves the division of the entire count of accurately categorized pixels by the overall count of pixels included in the image. The Kappa coefficient evaluates the level of agreement between observed and expected classifications, taking into account the potential for chance agreement as shown in equations 1 and 2. [25, 26].

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where TP is the true positives, TN is the true negatives, FP is the false positives, and FN is the false negatives.

$$Kappa = \frac{c \times s - \sum_k^K pk \times tk}{s^2 - \sum_k^K pk \times tk} \quad (2)$$

Where:

- $c = \sum_k^K C_{kk}$ the total number of elements correctly predicted
- $s = \sum_i^K \sum_j^K C_{ij}$ he total number of elements
- $pk = \sum_i^K C_{ki}$ the number of times that class k was predicted (column total)
- $tk = \sum_i^K C_{ik}$ the number of times that class k truly occurs (row total)

Verified that the Kappa index value is between (0 - 1) if it is equal (0). This shows that there is a big difference between the classification outputs and the reference results. On the other hand, if the value is equal to (1), there is a good agreement, while if the value varies from (0.4 - 0.8), the precision is medium, and the low value corresponds to a randomized classification [25, 26].

3 RESULTS AND DISCUSSION

3.1 Thematic map classification results

Using (SVM) algorithm, supervised classifications were done for images using ENVI 5.3v. Results of classification has been converted to shape files to deal with in the Arc GIS 10.8v and creating of thematic maps that classified into five main classes based on visual interpretation and visit the field of the study area, containing : urban areas ,vegetation, soil, asphalt roads, bodies of water as shown in Figure (9).

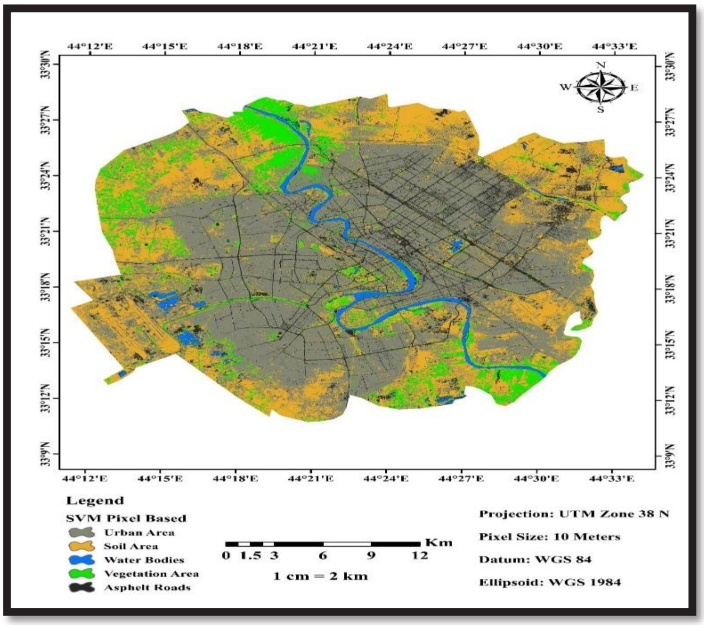

Fig. 9. Thematic map using (SVM)

3.2 Results of Areas calculation and percentages for classes:

Table (2) shows the calculation of Area and percentages of each class for the study area. The majority class reported was vegetation area, which accounted for over 44.85%. Sources of water, mainly rivers and branches, made up just 5.12 % of the total area, with soil include an area that does not have vegetation cover, accounting for another 14.53 %. With 31.38 %, the urban class was the second highest. Although it covered over 34.367 km^2 in the actual area, asphalt road was the least recognized class, accounting for nearly 4.12 %.

Table 2. Calculation of Area and percentages of classes

Classes	Area (Km²)	Percent. %
Urban	261.559	31 %
Soil Area	121.057	15 %
Water Bodies	42.651	5 %
Vegetation Area	373.762	45 %
Asphalt Roads	34.367	4 %
Total	833.397	100%

3.3 Accuracy Assessment of Classification and Validation results:

After the classification technique using the ENVI 5.3v software has been completed, the results of the accuracy of such algorithm images have been tested and checked and shown to be approved since the Kappa index is greater than (0.8), see the confusion matrix in Table (3) below for five different classes for the study area.

Overall, SVM classification produced an overall accuracy 87.61% and a kappa index 0.845 (Table3). In (Table 3), It is noted that approximately (12000) samples have been chosen for each of the five classes in the research area, at a rate of (2400) samples per class, in order to systematically and extensively represent the region. It can be seen that three classes recorded the greatest amount of misclassification using the SVM. Asphalt road has a very low user's accuracy of 85.59%, which means that approximately 15% of pixels classified as asphalt road were incorrectly classified, in this case, as water body, vegetation, urban and soil area. The soil area also had a low user's accuracy of 86.94%. The sampled pixels that were classified as soil area were, in actuality, urban, water body, vegetation, and in less degree asphalt road. Vegetation area was another class that experienced a high percentage of misclassification with a low producer's accuracy of 85.00%, which means that approximately 15% of the sampled pixels that are actually vegetation were classified as something else, in this case, water body, urban, asphalt road, and especially water body. Asphalt roads seem to have the highest producer accuracy of all the groups91.10%. Water bodies, on the other hand, have higher user accuracy than the other groups89.78%.

Table 3. Confusion matrix of (SVM) approach

Ground Truth (Pixels)							
Class	**Urban Area**	**Soil Area**	**Water Bodies**	**Vegetation Area**	**Asphalt Roads**	**Row total**	**User's accuracy**
Urban Area	2080	102	40	100	50	2372	87.69%
Soil Area	90	2090	90	74	60	2404	86.94%
Water Bodies	33	38	2002	108	49	2230	89.78%
Vegetation Area	69	50	110	2085	48	2362	88.27%
Asphalt Roads	86	85	100	86	2120	2477	85.59%
Column Total	2358	2365	2342	2453	2327	11845	
Producer's accuracy	88.21%	88.37%	85.48%	85.00%	91.10%		
Overall accuracy = (10337/11845) = 87.61%							
Kappa index of Agreement = 0.845							

Based on these results above, the accuracy assessment of land use maps classification by SVM algorithm are acceptable because of Kappa index is higher than 0.80.

4 Conclusions

This research offers significant contributions by assessing the accuracy of supervised classification SVM algorithm to extract of lands maps from satellite images in Baghdad city using remote sensing and GIS. The findings highlight efficiency of employing satellite imagery and (SVM) algorithm for accurately extracting land use and calculating their areas of classes with an overall accuracy 87.61 % and Kappa index 0.845. The consequences of the study's findings are significant for the sustainable management of the study area. These findings can provide valuable insights for decision-making in areas such as water resource management, land-use planning, and environmental monitoring. It is important to continue comparing the merits of each of these approaches with different types of LU/LC and with different types of imagery. To recommended that using the SVM algorithm to detect LU/LC to create a geo-database by integrating RS and GIS for all Iraq cities and compare with other classification algorithms.

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